A Neuro-Fuzzy Approach to Classification of ECG Signals for Ischemic Heart Disease Diagnosis

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ABSTRACT

The paper focuses on the neuro-fuzzy classifier called ***Fuzzy-Gaussian Neural Network (FGNN)*** *to recognize the ECG signals for Ischemic Heart Disease (IHD) diagnosis. The proposed ECG processing cascade has two main stages: (a) Feature extraction from the QRST zone of ECG signals using either the Principal Component Analysis (PCA) or the Discrete Cosine Transform (DCT); (b) Pattern classification for IHD diagnosis using the FGNN . We have performed the software implementation and have experimented the proposed neuro-fuzzy model for IHD diagnosis. We have used an ECG database of 40 subjects , where 20 subjects are IHD patients and the other 20 are normal ones. The best performance has been of 100% IHD recognition score. The result is exciting as much as we have used only one lead (V5) of ECG records as input data, while the current diagnosis approaches require the set of 12 lead ECG signals!*

1 INTRODUCTION

The *Ischemic (Ischaemic) Heart Disease (IHD)****,*** otherwise known as Coronary Artery Disease, is a condition that affects the supply of the blood to the heart. IHD is the most common cause of death in several countries around the world. Recently, there are many approaches involving techniques for computer processing of 12 lead electrocardiograms (ECG), in order to diagnose a certain disease. A first group of methods to interpret the ECG significance uses a morphological analysis. For example, myocardial ischemia may produce a flat or inverted T wave, that is classical narrow and symmetrical. A second group of techniques for computer analysis of ECG uses statistical models. In [2], a statistical model and the corresponding experimental results are presented for the classification of ECG patterns to diagnose the Ischemic Heart Disease (IHD). Last years, a third category of methods corresponding to *neural models* becomes a powerful concurrent to statistical ones for ECG signal classification [5 - 7].

On the other side, the hybrid systems of *fuzzy logic* and *neural networks* [4] often referred as *fuzzy neural networks)* represent exciting models of *computational intelligence* with direct applications in pattern recognition, approximation, and control. We further perform the ECG signal classification for IHD diagnosis using the neuro-fuzzy classifier called **Fuzzy-Gaussian Neural Network (FGNN**), that has been proposed in [1] by Neagoe and Iatan for face recognition. FGNN has been obtained as a *modified version* of the fuzzy neural network described by Chen and Teng in [3], as identifier in control systems; this network is transformed in [1] from an *identifier* into the *performing classifier* called *Fuzzy Gaussian Neural Network (FGNN).* We have applied this model here in an ECG recognition cascade for IHD diagnosis having the following processing stages: (a) feature extraction using either Principal Component Analysis (PCA) or Discrete Cosine Transform (DCT); (b) FGNN as a classifier. The results of computer simulation are given.

2 FUZZY GAUSSIAN NEURAL NETWORK (FGNN)

2.1 Architecture

The four-layer structure of the Fuzzy-Gaussian Neural Network (FGNN) described in [1] is shown in Fig. 1. It represents a modified version the fuzzy neural network presented in [3], by transforming the function of approximation into a function of *classification*. The change affects only the equations of the fourth layer, while the structure diagram is similar. Its construction is based on fuzzy rules of the form

$\Re_j$: If x_1 *is* A_1^j *and* x_2 *is* A_2^j ... *and* x_m *is* A_m^j,

then y_1 *is* $\beta_1^j, \ldots, y_M$ *is* β_M^j,

where m is the dimension of the input vectors (number of retained features), and j is the rule index (j=1,…, K). The number of output neurons (of the fourth layer) corresponds to the number of classes and it is equal to M. The FGNN keeps the advantages of the original fuzzy net described by Chen and Teng [3] for identification in control systems: (a) its structure allows us to construct the fuzzy system rule by rule; (b) if the prior knowledge of an expert is available, then we can directly add some rule nodes and term nodes; (c) the number of rules do not increase exponentially with the number of inputs; (d) elimination of redundant nodes rule by rule.

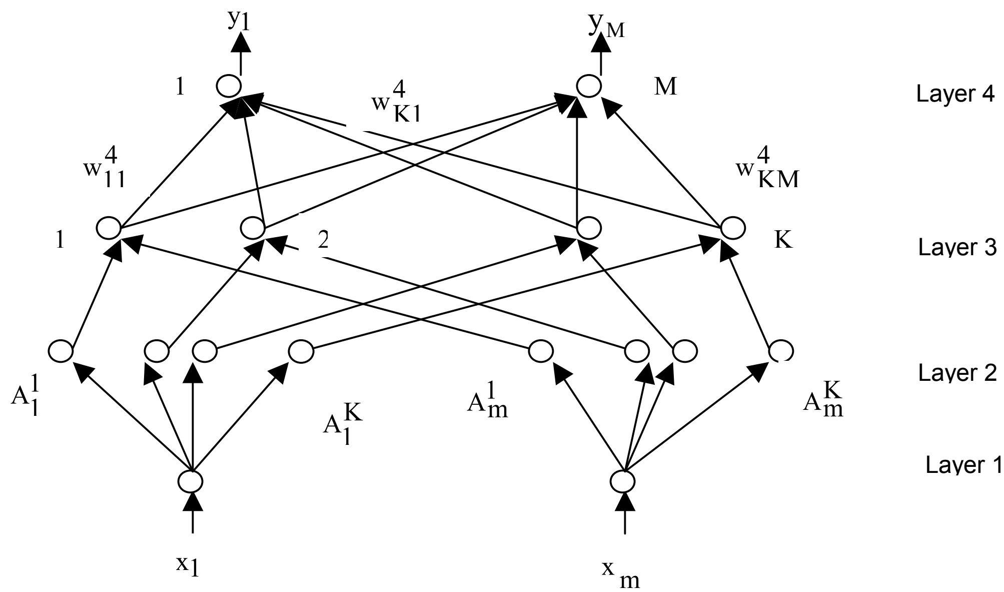

Figure 1. Structure of FGNN

Each neuron performs two actions using two different functions. The first is the aggregation function $g^k(\;)$, which computes the net input

Net input= $g^k\left(x^k; W^k\right)$,

where the superscript indicates the layer number (k=1, .., 4), x^k is the input vector and W^k is the weight vector. The second function is the nonlinear activation function $f^k(\;)$, which gives

Output= $O_i^k = f^k\left(g^k\right)$,

where O_i^k is the i-th output of the k-th layer.

2.2 Basic Equations

• Input level (level 1)

The neurons of the first level only transmit the information to the next level. The output

$Op_i^1 = x_{pi}^1$ (i=1, …, m)

is equal to the input, m is the number of neurons belonging to the firs level and p is the index of the input vector (p=1, …,K). The corresponding equations are $g_{pi}^1\left(x_{pi}^1\right) = x_{pi}^1$, (1)

$$O_{pi}^1 = f_i^1\left(g_{pi}^1\right) = g_{pi}^1\left(x_{pi}^1\right),\ i=1, .., m. \qquad (2)$$

•Linguistic Term Layer (level 2)

Each neuron performs a **Gaussian** membership function

$$g_{pij}^2\left(x_{pi}^2; m_{ij}; \sigma_{ij}\right) = -\frac{\left(x_{pi}^2 - m_{ij}\right)^2}{\sigma^2_{ij}}, \qquad (3)$$

$$O_{pij}^2 = f_{ij}^2\left(g_{pij}^2\right) = \exp\left(g_{pij}^2\right) = \exp\left[-\frac{\left(x_{pi}^2 - m_{ij}\right)^2}{\sigma^2_{ij}}\right] \qquad (4)$$

where the corresponding weights to be refined m_{ij} and σ_{ij} denote the mean and variance with respect to A_i^j (i= 1, …, m, j=1, …, K). The number of neurons characterizing this level is m*K. Each input x_{pi}^2 is transformed by this layer into a *fuzzy membership degree*.

• Rule Layer (level 3)

This layer computes the antecedent matching by the product operation, according to the relations

$$g_{pj}^3\left(x_{pij}^3; W_{ij}^3\right) = \prod_{i=1}^{n} W_{ij}^3 * x_{pij}^3, \qquad (5)$$

$$O_{pj}^3 = f_j^3\left(g_{pj}^3\right) = g_{pj}^3\left(x_{pij}^3; W_{ij}^3\right), \qquad (6)$$

where W_{ij}^3 is the connection weight between the i-th node of the second level (i=1, …, m) and the j-th neuron of the third level (j=1, .., K). Assume W_{ij}^3=1, $(\forall)$ i=1, .., m, j=1, …, K.

•Output Level (level 4)

This level performs the defuzzification

$$g_{pj}^4\left(x_{pi}^4; W_{ij}^4\right) = \sum_{i=1}^{K} W_{ij}^4 * x_{pi}^4. \qquad (7)$$

We introduce at this level a sigmoid activation function in order to apply the FGNN for classification

$$y_{pj}^4 = f_j^4\left(g_{pj}^4\right) = \frac{1}{1 + \exp\left(-\lambda * g_{pj}^4\left(x_{pi}^4; W_{ij}^4\right)\right)} \qquad (8)$$

where W_{ij}^4 is the connection between the neuron i (i=1, …, K) of the third level and the neuron j (j=1, … , M) of the fourth level.

The *FGNN supervised training algorithm* is of type "back-propagation".

3 EXPERIMENTAL RESULTS

3.1 ECG Database

For experimenting the proposed FGNN model, we have used an ECG database of 40 subjects : 20 patients of Ischemic Heart Disease (IHD) and other 20 normal subjects. The ECG database is divided into the training lot and the test lot, each with 20 subjects of both categories (10 normal and 10 with IHD). We have considered that the *significant information for IHD diagnosis is concentrated on the QRST zone of the lead V5 only.* For acquisition of ECG signals, a sampling frequency of 1000 Hz and a resolution of 11 bits/sample have been chosen. A sequence of heartbeats of 9.9 s of the lead V5 has been stored for each subject (9999 samples). First ECG processing step has consisted of extracting the useful information from a record, namely construction of a characteristic waveform called prototype [2], [8]. The *selected QRST* zone of the prototype has been normalized to n=128 samples (Figs. 2 and 5).

3.2 Feature Extraction

- **Feature extraction using PCA**

The *Principal Component Analysis (PCA)* stage is equivalent to the computation of the Karhunen-Loeve Transform [8]. We have computed the covariance matrix of the whole training set of 20 vectors $\mathbf{X} \in \boldsymbol{R}^{128}$, the *eigenvalues* and the *eigenvectors.* We have ordered the eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_{127} \geq \lambda_{128}$, and have computed the energy preservation factor E, by retaining only "m" eigenvalues. The variation of the factor E as a function of **m** is given in Table 1; for example, we can reduce the space dimension from 128 to 28, by preserving 100 % of the signal energy (Table 1). Examples of PCA (amplitude spectrum) are given in Figs. 3 and 6.

- **Feature extraction using DCT**

The *Discrete Cosine Transform (DCT)* applied for feature extraction has the advantage of reducing the computational effort (there are several algorithms available [9]), but it leads to a slightly less energy-preserving factor by comparison to PCA. The simulation results given in Table 1 show that one can reduce the space dimension from 128 to 28 using DCT, by preserving 98.42% of the signal energy. Examples of DCT (amplitude spectrum) are given in Figs. 4 and 7.

3.3 Classification with FGNN for IHD Diagnosis

The FGNN classifier is applied for IHD diagnosis in the m- dimensional space of the retained features. We have experimented the neuro-fuzzy classifier for the two variants of feature extraction (PCA and DCT) choosing the following numbers of retained features: m=10, 28, 40 and 50. The recognition performances are shown in Table 2 and Fig.8.

4 CONCLUDING REMARKS

1. The paper presents an ECG classification approach for IHD diagnosis using a neuro-fuzzy model called *Fuzzy-Gaussian Neural Network (FGNN).*
2. The ECG processing cascade has two main stages: (a) feature extraction using either PCA or DCT; (b) ECG pattern classification using FGNN.
3. The promising classification performance of FGNN may be explained by the fact that the classifier is a *hybrid system* of fuzzy logic and a powerful Gaussian network.
4. By choosing PCA as a feature selection technique, for the training lot of 20 ECG-QRST prototypes (10 normal subjects and 10 afflicted with IHD), one can reduce the space dimension from 128 to 28 by preserving 100% of the signal energy (Table 1). By considering that the initial 12 lead ECG record during 9.9 s is reduced to the QRST zone of one lead only (128 samples), the real compression is from 12 x 9 900=118 800 samples to 28 coefficients, implying a compression ratio of 4 242:1!
5. If one chooses the DCT for the same space dimensionality reduction, the energy preservation ratio decreases to 98.42% (Table 1).
6. In Table 2 and Fig. 8, one can evaluate *the very good recognition performance (100%*!) of the FGNN by choosing PCA as a feature extraction stage with m=50 features. *The result is exciting as much as we have used only one lead (V5) of ECG records as input data, while the current approaches use the computer processing of 12 lead ECG signals for diagnosis!*
7. For the same number of retained features "m", the DCT usually leads to a less recognition rate than PCA (for example, for m=50, one obtains a recognition score of 90% for DCT and 100% for PCA; for m=28, one obtains a recognition score of 90% for DCT and 95% for PCA).
8. Usually, by increasing the number of retained features "m", the recognition score increases (Table 2 and Fig. 8).

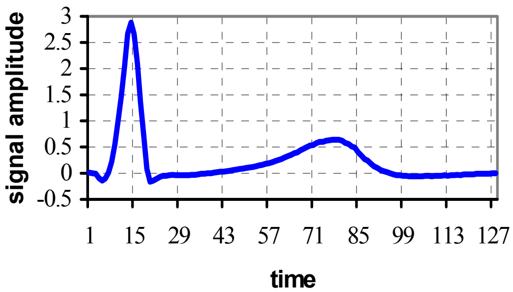

Fig. 2. ECG-QRST prototype corresponding to a normal subject

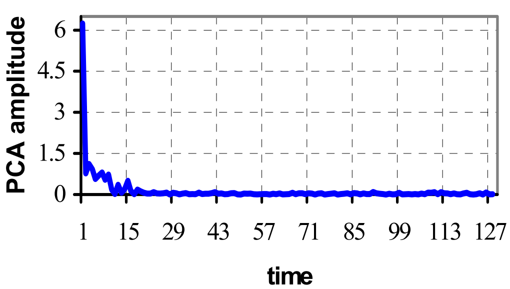

Fig. 3. PCA of the prototype given in Fig. 2.

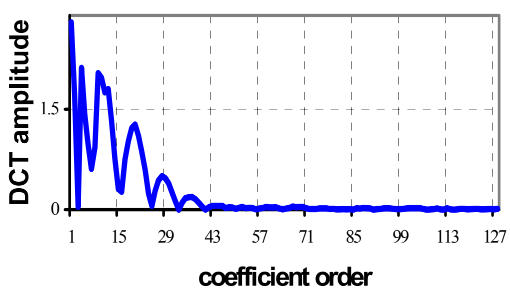

Fig. 4. DCT of the prototype given in Fig. 2.

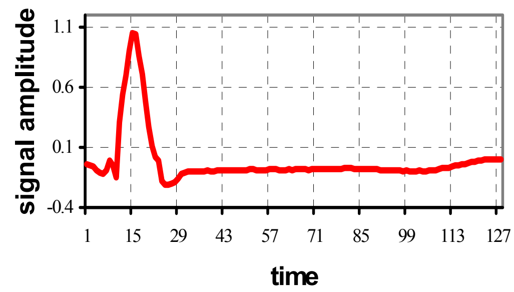

Fig. 5. ECG-QRST prototype corresponding to a patient afflicted with IHD (remark the flat T area)

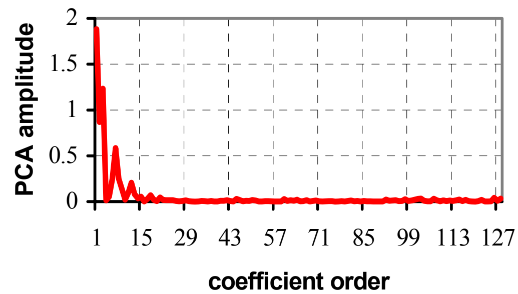

Fig. 6. PCA of the prototype given in Fig. 5

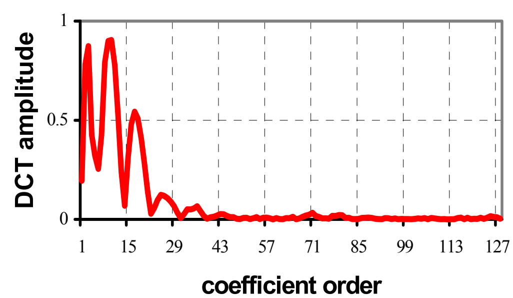

Fig. 7. DCT of the prototype given in Fig. 5

Table 1. Energy preservation factor of PCA versus DCT as a function of the number of features m .

Number of Features (m)		10	28	30	38	40	48	50	58	60	68
Energy preservation factor E(%)	**PCA**	99.64	100	100	100	100	100	100	100	100	100
	DCT	76.14	98.42	98.79	99.58	99.65	99.84	99.86	99.90	99.91	99.93

Table 2. Recognition score of the FGNN classifier as a function of the number of features m.

Number of retained principal components m	Type of feature extraction	Recognition score for the training lot (%)	Recognition score for the test lot (%)	Number of training epochs
10	PCA	95	85	402
10	DCT	95	85	346
28	PCA	95	95	1837
28	DCT	100	90	785
40	PCA	100	90	708
40	DCT	100	90	379
50	PCA	100	100	1041
50	DCT	100	90	183

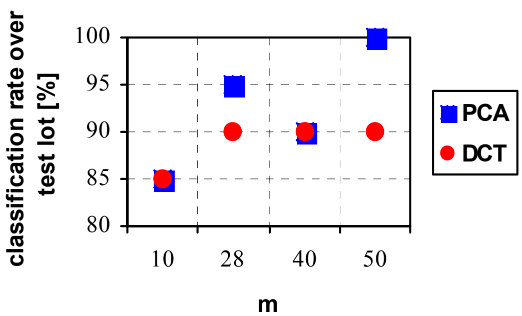

Fig. 8. Recognition score for IHD (%) over the test lot as a function of the number of features

9. The DCT requires a less computational complexity than PCA, since it has several fast algorithms available.
10. Moreover, the network training time decreases for DCT by comparison to PCA (Table 2). For example, choosing m=50 features, the number of necessary training epochs is 1041 for PCA, leading to a recognition rate of 100% and the number of epochs becomes 141 for DCT, leading to the recognition rate of 90%.

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